

**A Final Report  
Grant No. NGT-70172**

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**ARTIFICIAL NEURAL NETWORK IMPLEMENTATION OF  
A NEAR-IDEAL ERROR PREDICTION CONTROLLER**

**Submitted to:**

**National Aeronautics and Space Administration  
Langley Research Center  
Hampton, Virginia 23665**

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**DEPARTMENT OF ELECTRICAL ENGINEERING**

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SCHOOL OF

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**UNIVERSITY OF VIRGINIA**  
**School of Engineering and Applied Science**

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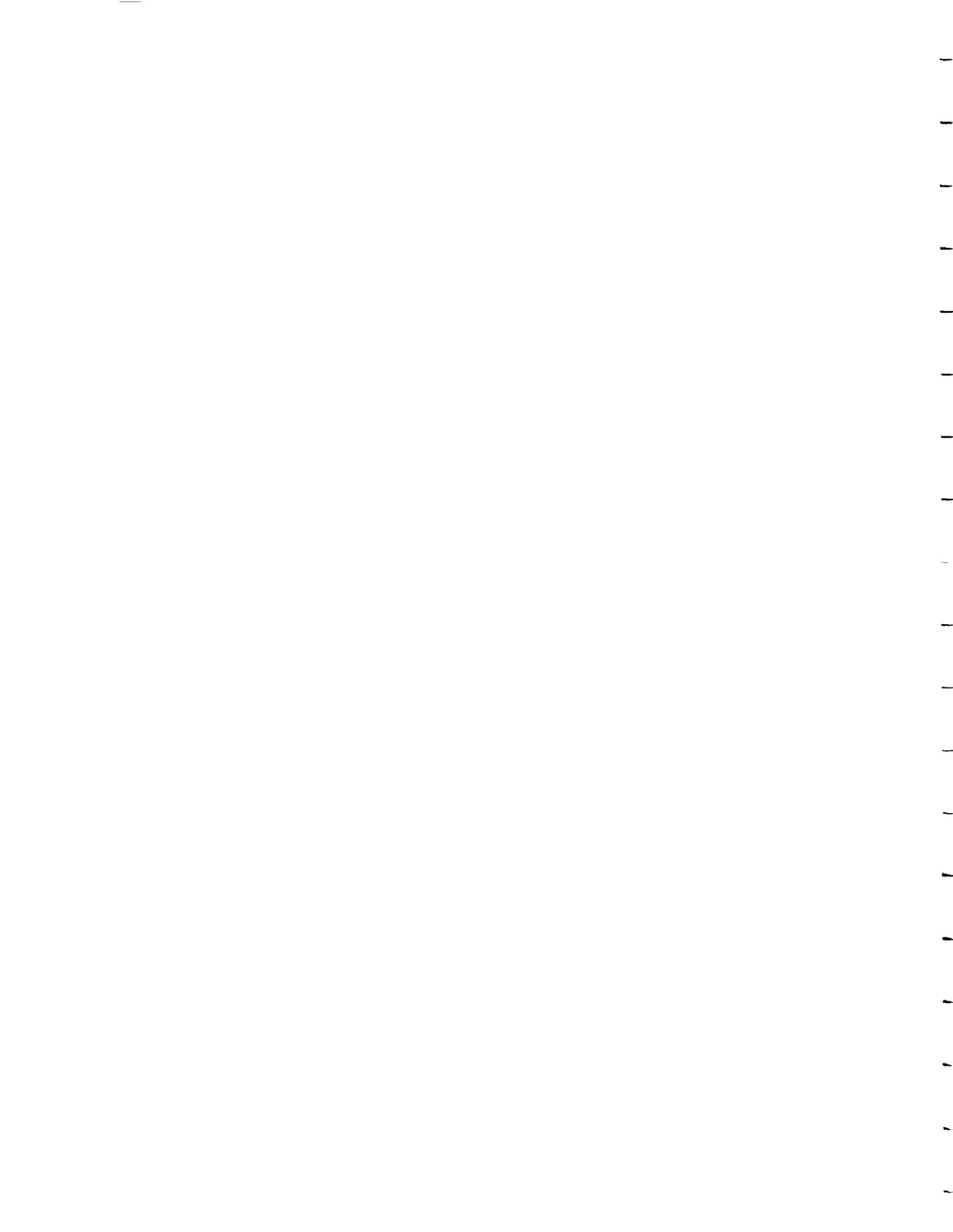


## **INTRODUCTION**

A theory has been developed at the University of Virginia which explains the effects of including an ideal predictor in the forward loop of a linear error-sampled system. It has been shown that the presence of this ideal predictor tends to stabilize the class of systems considered. A prediction controller is merely a system which anticipates a signal or part of a signal before it actually occurs. It is understood that an exact prediction controller is physically unrealizable. However, in systems where the input tends to be repetitive or limited, (i. e. not random) near ideal prediction is possible. In order for the controller to act as a stability compensator, the predictor must be designed in a way that allows it to learn the expected error response of the system. In this way, an unstable system will become stable by including the predicted error in the system transfer function.

Previous and current prediction controllers include pattern recognition developments and fast-time simulation which are applicable to the analysis of linear sampled data type systems. The use of pattern recognition techniques, along with a template matching scheme, has been proposed as one realizable type of near-ideal prediction. Since many, if not most, systems are repeatedly subjected to similar inputs, it was proposed that an adaptive mechanism be used to "learn" the correct predicted error response. Once the system has learned the response of all the expected inputs, it is necessary only to recognize the type of input with a template matching mechanism and then to use the correct predicted error to drive the system.

This report will suggest an alternate approach to the realization of a near-ideal error prediction controller, one designed using Neural Networks. Neural Networks are good

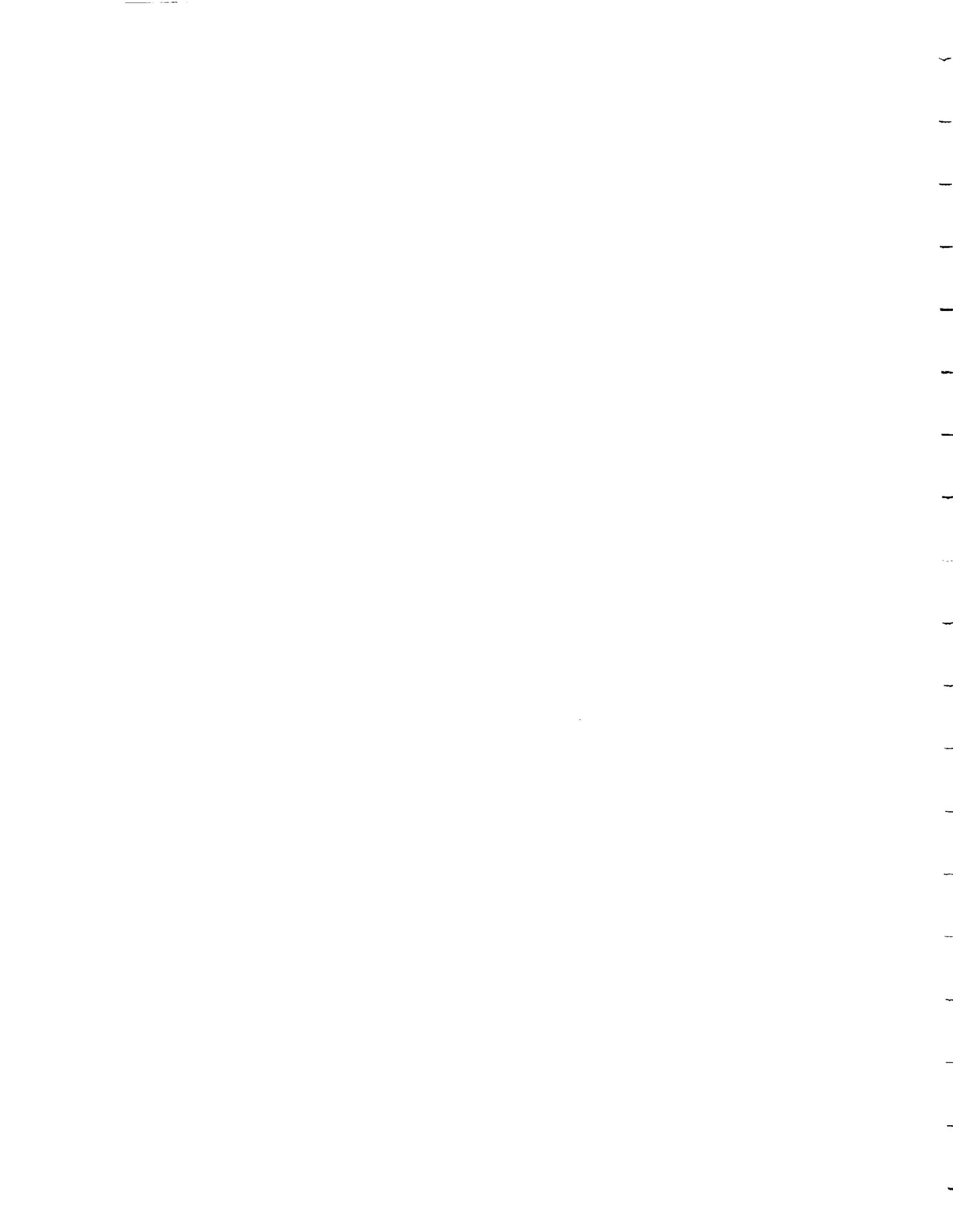


at recognizing patterns such as system responses and the back-propagation architecture makes use of a template matching scheme. In using this type of error prediction, it is assumed that the system error responses be known for a particular input and modeled plant. These responses are used in the error prediction controller. An analysis was done on the general dynamic behavior that results from including a digital error predictor in a control loop and these results were compared to those including the near-ideal Neural Network error predictor. This analysis was done for a second and third order system.

### **BACK-PROPAGATION NEURAL NETWORK**

A neural network, as defined by Hecht-Nielsen, is a parallel distributed information processing structure consisting of processing elements (which can possess a local memory and can carry out localized information processing operations) interconnected together with unidirectional signal channels called connections. Each processing element has a single output connection which branches into as many collateral connections as desired (each carrying the same signal - the processing element output signal). The processing element output signal can be of any mathematical type desired (sigmoid in this case). All of the processing that goes on within each processing element must be completely local.

A three layer back-propagation neural network was used to implement a near-ideal error predictor controller. Back-propagation is the most widely used neural network architecture. It is a hierarchical design consisting of fully interconnected layers of processing units or neurons. Back-propagation is a mapping architecture. The real power of the back-propagation rule comes from its assignment of deltas to hidden layers



that receive no direct feedback from training patterns in the outside world. These deltas, in turn, influence the modification of weights to connections leading into the hidden layers.

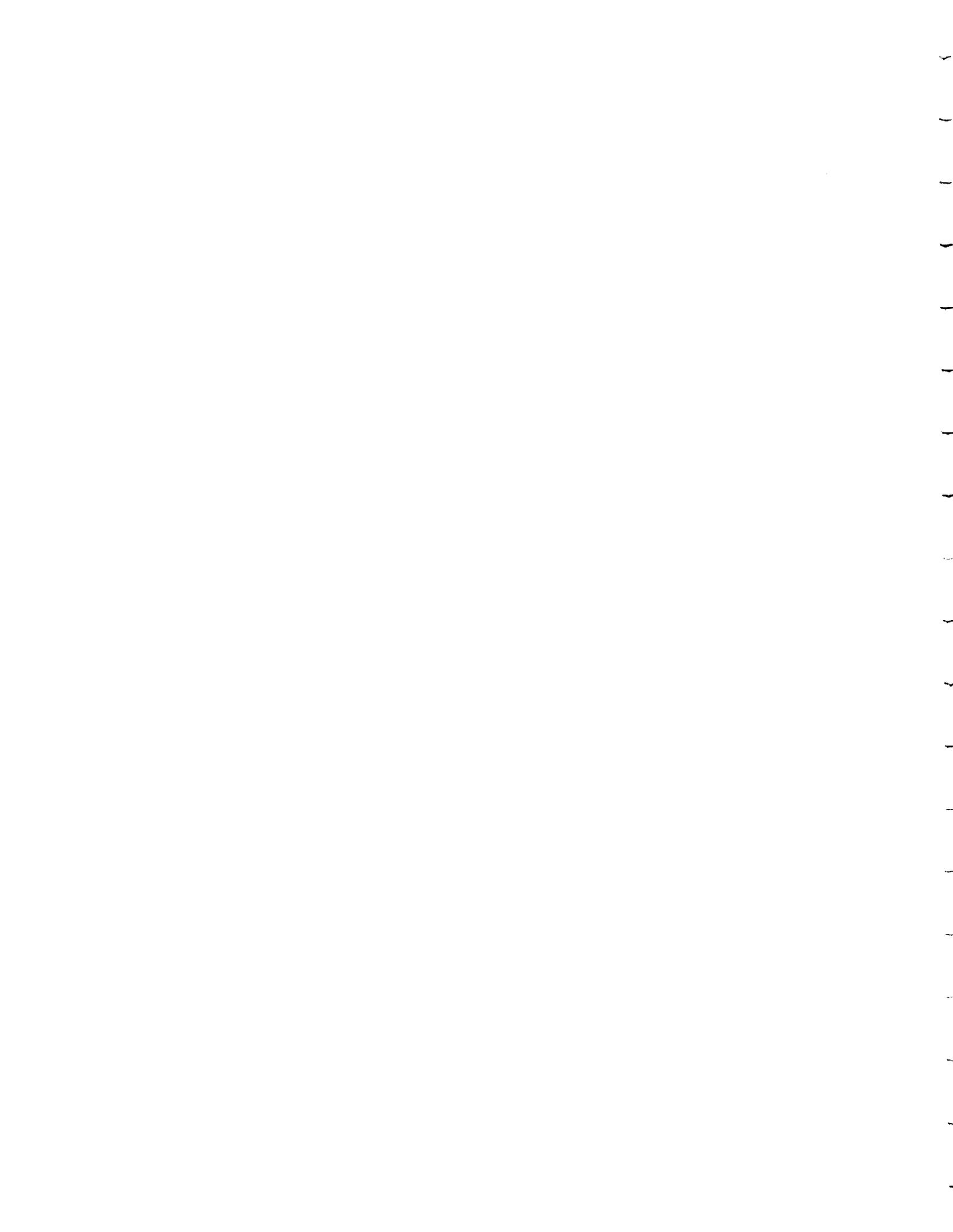
The delta for a hidden layer is computed as follows

$$\delta_{pj} = f'_j(I_{pj}) \sum_k \delta_{pk} w_{kj}$$

Notice this definition uses the derivative to its squashing function (sigmoid) multiplied by the weighted sum of the deltas to which the neuron sends activation via outgoing connections.

The basic idea behind this computation of deltas for internal neurons is to propagate back through the system errors that are based on observed discrepancies between the values of desired output neurons and a training pattern. The deltas are first computed for the output neurons, and these are then propagated backward to all layers pointing to the output neuron in the layer below. These neurons, in turn, propagate their received deltas backward to neurons that point to them, and so on, until the input level is reached. These deltas then drive the networks's weight changes in much the same way as with the basic delta rule described by Hecht-Nielsen.

In scheduling a network's operation during training, two passes are needed to complete one iteration. The first is the forward pass which begins by inserting the inputs into layer 1 of the neural network. This is often done by using an input vector ( $I$ ). The processing elements of the first layer then transmit all components of the input vector to all of the units of the second layer. This is continued until the final layer outputs the components of the output vector ( $O$ ) which represent the network's estimate of the desired output vector ( $D$ ). At this point the backward pass is initiated. The output sums



of the final layer compute their  $\delta k$ 's and transmit these to their planets. The planets then update their delta values of weights and then transmit the values  $w_{kij}^{old} \delta k_i$  to the suns of the previous row. This process continues until the planets of the first hidden layer have been updated. The cycle can then be repeated. Iterations are repeated until the network has satisfied a predetermined level of performance. Once training is complete, actual operation on test sets does not require the use of the backward pass.

In training the neural network for near-ideal error prediction, the input vector was the integer number of samples,  $p$ , represented as a binary number of 1's and 0's. The desired output vector ( $D$ ), was the predicted error values needed for that particular number of samples for a given  $G_p(s)$  and input. Only unit step inputs were analyzed. The output vector values were scaled between 0 and 1 and then weighted back upon completion of training. The predetermined level of performance was within .001 accuracy.

## **RESULTS**

An analysis was done on a second and third order system, and unit step responses of both these systems without prediction compensation were obtained. Both systems were very unstable. There the results of system output for both plant systems using varying degrees of prediction compensation were obtained. Only the first nine sampling instants were considered. Results for ideal prediction and near-ideal prediction using the neural network were compared. The results were very close with very good accuracy for one step prediction. Second and third step prediction using the neural network does not stabilize the system. Unit step responses of the near-ideal error



prediction compensated systems of the second and third order systems respectively with one step prediction were obtained.

## **CONCLUSION**

An alternate approach to the realization of a near-ideal error prediction controller, one designed using Neural Networks was presented. The unit step response of two different plants was analyzed by comparing responses with and without prediction compensation. Ideal versus near-ideal error prediction results were also presented. For the two systems chosen, one step prediction did improve the unit step response. It appeared that using two or three step prediction did not improve the system response to a unit step.

Further work should investigate the effect of using other inputs such as ramp functions. Also, it would be desirable to be able to simulate the prediction compensation transfer function in its entirety which takes as inputs the plant and predicted error.

A comprehensive report containing descriptions, data and graphics is available from the Department of Electrical Engineering, University of Virginia.



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